

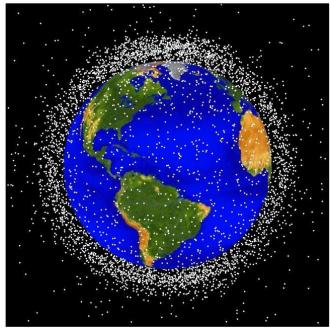
# Distributed Fast Motion Planning for Spacecraft Swarms in Cluttered Environments

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#### Motivation

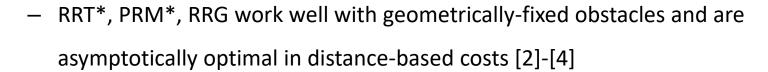
- Objective: Trajectory planning of multi-agent systems (or swarms) in an obstacle rich environment
  - Navigation through debris fields, asteroid belt
  - Multi-satellite missions, docking with uncooperative targets
- Assumption: Obstacle field is known a priori
- Multi-Agent Spherical Expansion and Sequential
   Convex Programming (Multi-Agent SE-SCP) algorithm:
  - Trajectory is compatible with spacecraft dynamics
  - Real-time implementation
  - Guarantee any-time local optimality





# Relevant Approaches in Literature

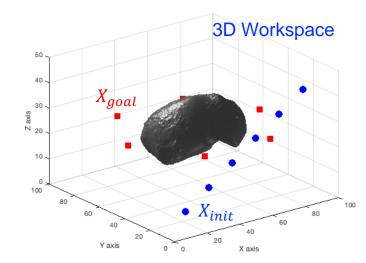
- Algorithms that discretize the workspace
  - Not suitable for incorporating dynamics
- Multi-spacecraft trajectory planning
  - Usually deals with cooperative obstacles [1]
- Sampling based algorithms in robotics



- Differential flatness technique used to incorporate dynamics [5]
- Weak guarantees of optimality (asymptotic optimality)



- [2] LaValle et. al., "Randomized kinodynamic planning," IJRR, 2001
- [3] Kavraki, "Probabilistic roadmaps for path planning in high-dimensional configuration spaces," IEEE TRO, 1996
- [4] Karaman et. al. "Sampling-based algorithms for optimal motion planning," IJRR, 2011.
- [5] Kumar et. al., "Minimum snap trajectory generation and control for quadrotors," ICRA, 2011.



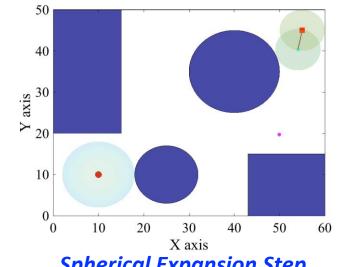
# Prior Work: SE-SCP Algorithm

- SE-SCP solution approach has 2 steps:
  - **Explore: Spherical Expansion step**
  - Optimize: Sequential Convex Programming (SCP) step

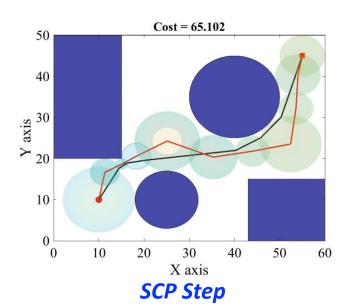
minimize cost subject to boundary conditions *linearized dynamics* trajectory goes through

spheres

- Any-time local optimality
- Asymptotic global optimality
  [1] F. Baldini et. al., "Fast Motion Planning for Agile Space Systems with Multiple Obstacles," AIAA/AAS Astrodynamics Specialist Conference, Long Beach, CA, September, 2016.



**Spherical Expansion Step** 



#### **Problem Statement**

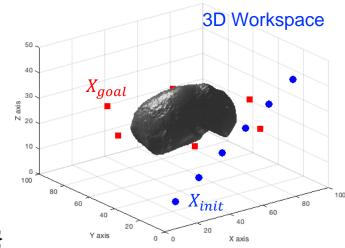
- 3D workspace  $\mathcal{X} \subset \mathbb{R}^3$  in LVLH frame
- Known stationary obstacles  $\mathcal{X}_{obs} \subset \mathcal{X}$
- N agents (spacecraft)
- Initial positions  $X_{init}^i \in \mathcal{X}, \ \forall i \in \{1, ..., N\}$





$$||Y_k^i - Y_k^j||_2 \ge r_{col}, \quad \forall i, j \in \{1, \dots, N\}, \quad \forall k \in \mathbb{N}$$

• The objective of the Multi-Agent SE-SCP algorithm is to ensure that all the N agents reach the N terminal positions while avoiding collisions with the obstacles and among themselves.



# Pseudo-code of Multi-Agent SE-SCP Alg.

Spherical Expansion
Step

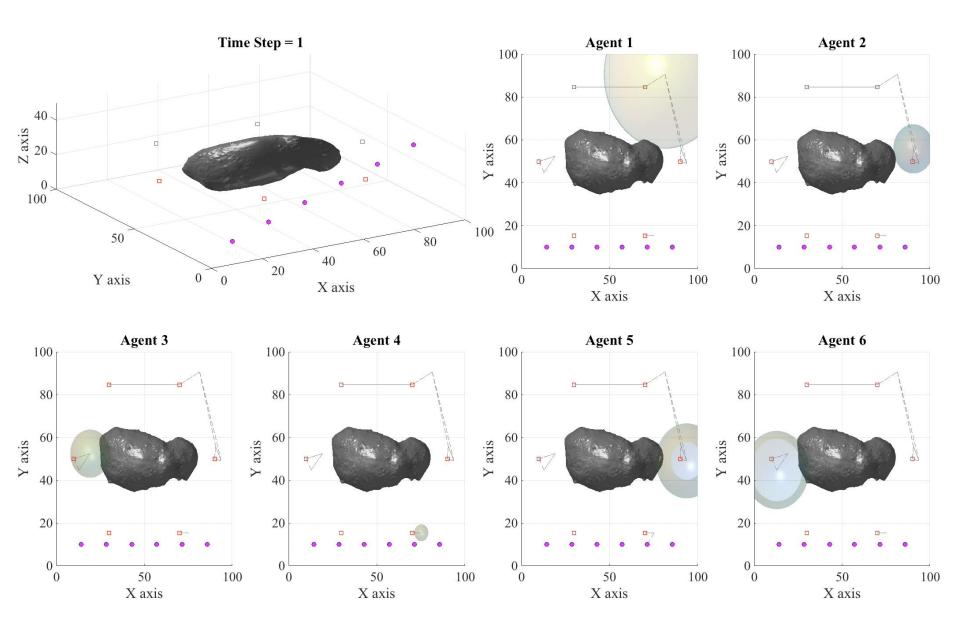
Sequential Convex Programming (SCP) Step

```
Algorithm 1 Multi-Agent SE–SCP Algorithm for the i^{th} agent
   1: r_{	ext{init}}^i \leftarrow 	ext{MinDistObs}(X_{	ext{init}}^i, \mathcal{X}_{	ext{obs}}),
                                                                                                \mathcal{V}^i \leftarrow \{X^i_{	ext{init}}[r^i_{	ext{init}}]\}
                                                                                                                                                                                                                                        > Initialization step
  2: for j = \{1, ..., N\} do
               r_{\mathrm{goal}}^j \leftarrow \mathtt{MinDistObs}(X_{\mathrm{goal}}^j, \mathcal{X}_{\mathrm{obs}}), \qquad \mathcal{V}^i \leftarrow \mathcal{V}^i \cup \{X_{\mathrm{goal}}^j[r_{\mathrm{goal}}^j]\}
 5: \mathcal{E}^i \leftarrow \emptyset, F^i_{\mathrm{reached}} \leftarrow 0, F^i_{\mathrm{connected}} \leftarrow 0, X^i_{\mathrm{term}} \leftarrow \emptyset
6: while F_{\mathrm{reached}} \neq 1 do
7: Y^\ell, X^\ell_{\mathrm{new}}, F^\ell_{\mathrm{connected}}, \forall \ell \in \{1, \dots, N\} \leftarrow \mathtt{AllAgentCommunicate}

▷ Spherical Expansion step

   8:
                for \ell = \{1,\ldots,N\}/\{i\} do
  9:
                          \hat{\mathcal{X}}_{\mathrm{obs}}^i = \hat{\mathcal{X}}_{\mathrm{obs}}^i \cup \mathtt{GenerateSphere}(Y^\ell, r_{\mathrm{col}} + r_{\mathrm{max}}), \qquad \mathcal{V}^i \leftarrow \mathcal{V}^i \cup \{X_{\mathrm{new}}^\ell[0]\}
 10:
 11:
 12:
                  \mathcal{V}_{	ext{new}}^i \leftarrow \emptyset
 13:
                  for all X_{\mathbf{v}}[r_{\mathbf{v}}] \in \mathcal{V}^i do
                         r_{\mathrm{v}} \leftarrow \mathtt{MinDistObs}(X_{\mathrm{v}}, \hat{\mathcal{X}}_{\mathrm{obs}}^{i}), \qquad \mathcal{V}_{\mathrm{new}}^{i} \leftarrow \mathcal{V}_{\mathrm{new}}^{i} \cup \{X_{\mathrm{v}}[r_{\mathrm{v}}]\}
 14:
 15:
                  \mathcal{V}^i \leftarrow \mathcal{V}^i_{\mathrm{new}}
 16:
 17:
                   X_{\mathrm{rand}} \leftarrow \texttt{GenerateSample}
 18:
                   X_{\text{nearest}} \leftarrow \text{NearestNode}(\mathcal{V}^i, X_{\text{rand}})
                  X_{\text{new}}^{i} \leftarrow \texttt{Steer}(X_{\text{rand}}, X_{\text{nearest}})
                                                                                                               \mathcal{V}^i \leftarrow \mathcal{V}^i \cup \{X_{\mathrm{new}}^i[r_{\mathrm{new}}^i]\}
 20:
                  r_{\text{new}}^i \leftarrow \texttt{MinDistObs}(X_{\text{new}}^i, \hat{\mathcal{X}}_{\text{obs}}^i),
21:
 22:
                  for all X_{\mathbf{v}}[r_{\mathbf{v}}], X_{\mathbf{w}}[r_{\mathbf{w}}] \in \mathcal{V}^i and X_{\mathbf{v}} \neq X_{\mathbf{w}} do
 23:
                         if \|X_{\mathbf{v}} - X_{\mathbf{w}}\|_2 \le r_{\mathbf{v}} + r_{\mathbf{w}} then
24:
                                  c_{	ext{v,w}} \leftarrow \texttt{EdgeCost}(X_{	ext{v}}, X_{	ext{w}}),
                                                                                                               c_{	ext{w,v}} \leftarrow \texttt{EdgeCost}(X_{	ext{w}}, X_{	ext{v}})
25:
                                  \mathcal{E}^i \leftarrow \mathcal{E}^i \cup \{\overrightarrow{X_{\mathbf{v}}} \overrightarrow{X_{\mathbf{w}}} [c_{\mathbf{v},\mathbf{w}}]\} \cup \{\overrightarrow{X_{\mathbf{w}}} \overrightarrow{X_{\mathbf{v}}} [c_{\mathbf{w},\mathbf{v}}]\}
 26:
27:
                  end for
 28:
                  if X_{\mathrm{term}}^i = \emptyset then
                                                                                                                                                                                          ▷ Sequential Convex Programming step
                         if \sum_{\ell=1}^{N} F_{\text{connected}}^{\ell} = N^2 then
 29:
                                                                                                                                  \mathcal{V}^i \leftarrow \mathcal{V}^i \cup \{X^i_{\mathrm{term}}[0]\}
30:
                                   X_{\text{term}}^{i} \leftarrow \texttt{DistributedAssignment},
31:
                          else
 32:
                                   F_{\text{connected}}^{i} \leftarrow 0
 33:
                                   for j = \{1, ..., N\} do
 34:
                                          P^{i,j}, c_{P^i,j} \leftarrow \mathtt{MinPath}(\mathcal{G}^i = (\mathcal{V}^i, \mathcal{E}^i), X^i_{\mathrm{init}}, X^j_{\mathrm{goal}})
 35:
                                          if c_{Pi,j} < \infty then
                                         F_{\text{connected}}^{i} \leftarrow F_{\text{connected}}^{i} + 1 end if
 36:
37:
38:
                                   end for
 39:
                          end if
 40:
                  else
                          \begin{aligned} & \text{if } X_{\text{term}}^i = Y^i \text{ then } \\ & F_{\text{reached}}^i \leftarrow 1, \end{aligned} 
41:
42:
43:
 44:
 45:
                                  P^i, c_{P^i} \leftarrow \texttt{MinPath}(\mathcal{G}^i = (\mathcal{V}^i, \mathcal{E}^i), Y^i, X^i_{\text{term}}), \qquad (\boldsymbol{x}^i_1, \boldsymbol{u}^i_1, c_{\boldsymbol{x}^i_1}) \leftarrow \texttt{OptimalTraj}(P^i)
 46:
                                  for k = \{1, ..., N_{SCP}\} do
                                          P_k^i \leftarrow \texttt{GeneratePath}(\boldsymbol{x}_k^i), \qquad (\boldsymbol{x}_{k+1}^i, \boldsymbol{u}_{k+1}^i, c_{\boldsymbol{x}_{k+1}^i}) \leftarrow \texttt{OptimalTraj}(P_k^i, \boldsymbol{x}_k^i, \boldsymbol{u}_k^i)
47:
 48:
                                  \pmb{x}^i \leftarrow \pmb{x}^i_{N_{SCP}+1}
 49:
50:
                          end if
51:
                  Y^i \leftarrow AgentMotion(x^i),
                                                                                        \mathcal{V}^i \leftarrow \mathcal{V}^i \cup \{Y^i[0]\}
 53: end while
```

### Solution of Multi-Agent SE-SCP Algorithm

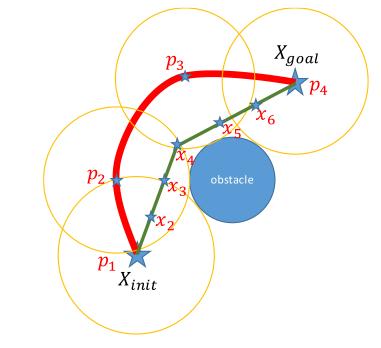


# Spherical Expansion Step



# Sequential Convex Programming Step

Given the nodes in a path and their corresponding radii, the convex optimization problem is written as:



#### **Problem 1:** Discrete-time Convex Optimal Motion Planning Problem

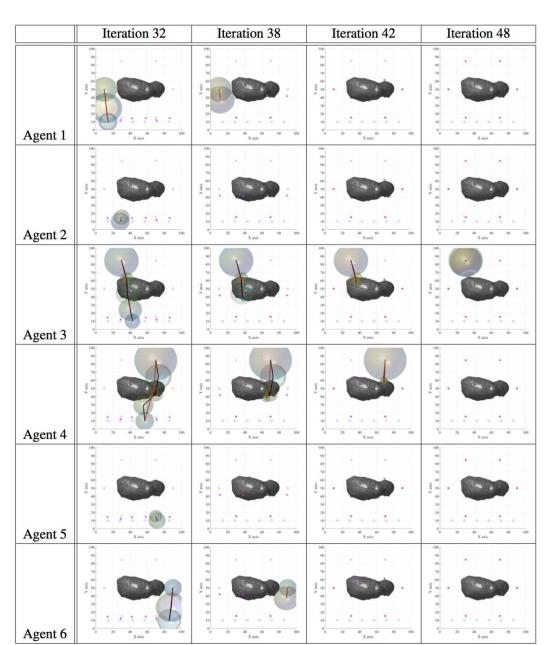
minimize cost

boundary condition

trajectory goes through spheres

linearized dynamics

# Sequential Convex Programming Step



#### Conclusions

- Multi-Agent SE-SCP algorithm:
  - Generates spacecraft trajectory through multiple geometricallyfixed obstacles
  - Two steps: the spherical expansion step and the sequential convex optimization step
  - Is any-time locally optimal and asymptotically global optimal
- Future work will focus on moving obstacles and limited FOV

# Thank You